DSCI402 Capstone Project: Survey of Time Series

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2. Try different roles in the process
3. Do something different

Time Series

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- **Time Series Analyses** - a type of regression that attempts to capture the correlation of the values w.r.t. time.

Project Objectives

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3. Create materials to demonstrate our learning

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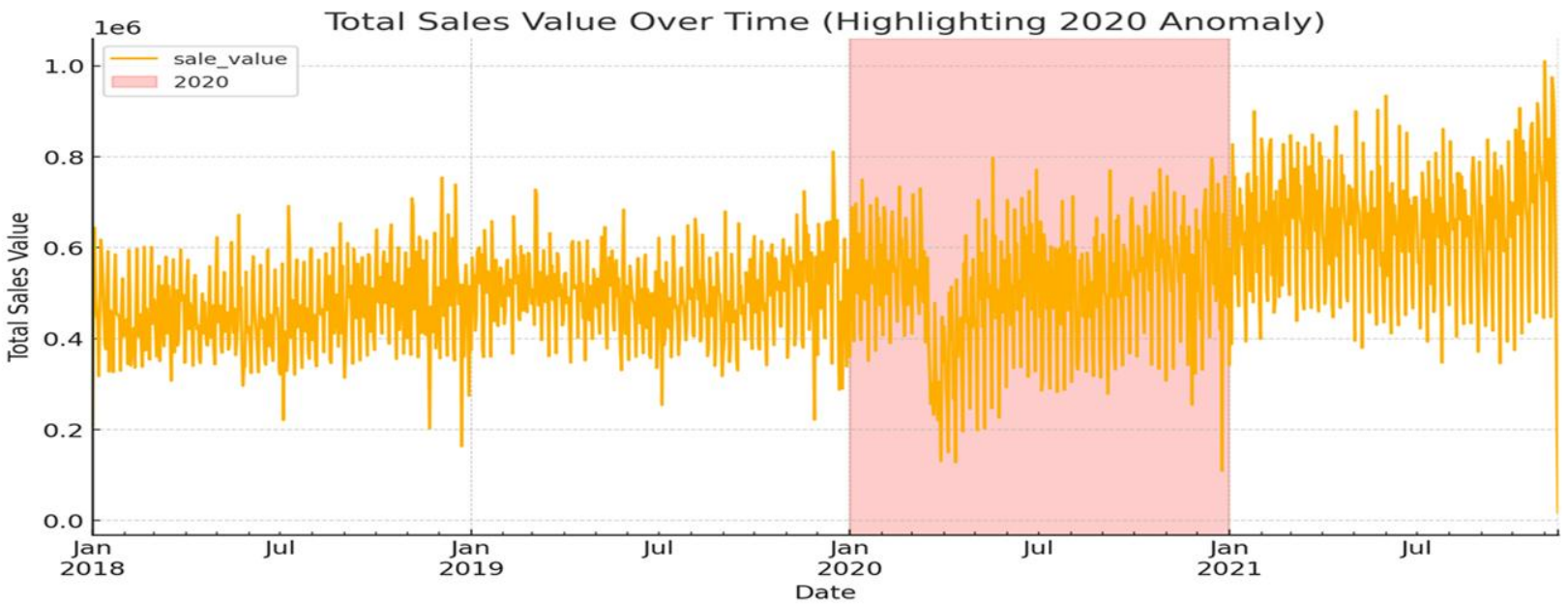
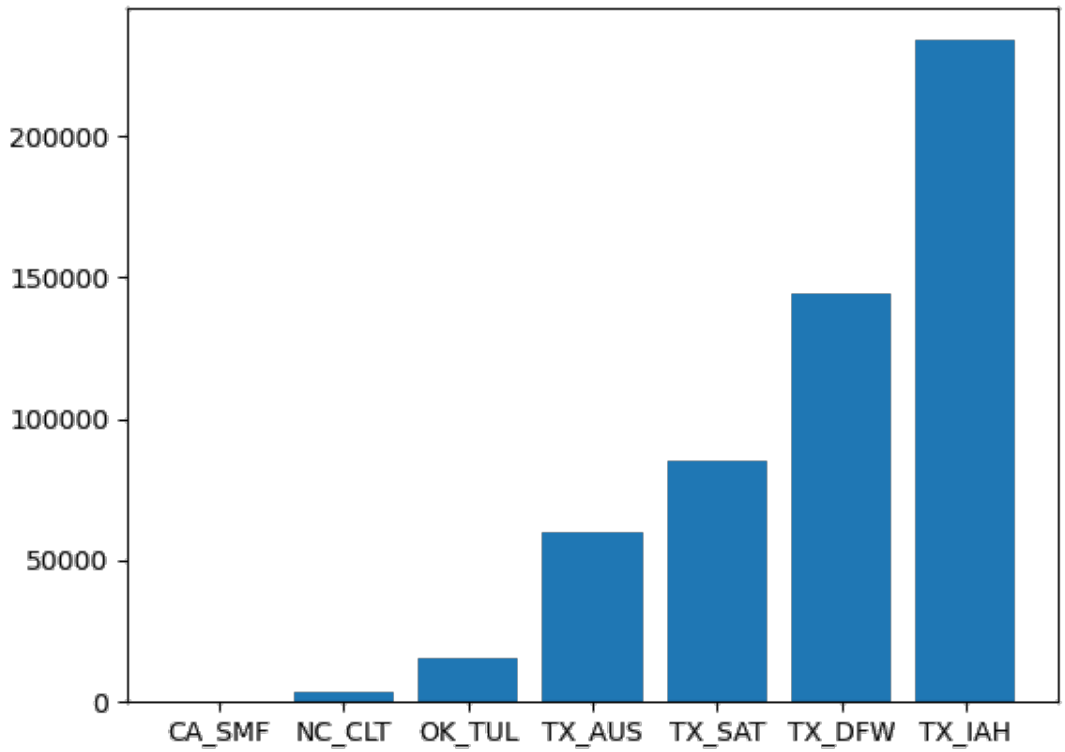
1. **Invoice Date** - the date for which the total sales were recorded
2. **Customer Code** - a code that uniquely identifies the customer. These codes were anonymized prior to receiving them in order to protect confidentiality of the original client.
3. **Channel Text** - a label that represented the sales channel. This was almost entirely anonymized, and did not reveal any insights.
4. **Blend** - The type of oil being sold. A categorical attribute that describing whether the oil is conventional or synthetic. This attribute was labelled internally as ”conventional/synthetic”
5. **Variety and Size** - details the oil type and packaging
6. **Sale Value** - the target attribute, the total sales recorded for that row

Data Overview



Spread of Locations



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- **Location Code** - allows preservation of regional trends

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- Data set split on location

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  - Explainable
- Deep Learning approach: **Prophet**
  - Neural Net based
  - Unexplainable - ”black box”

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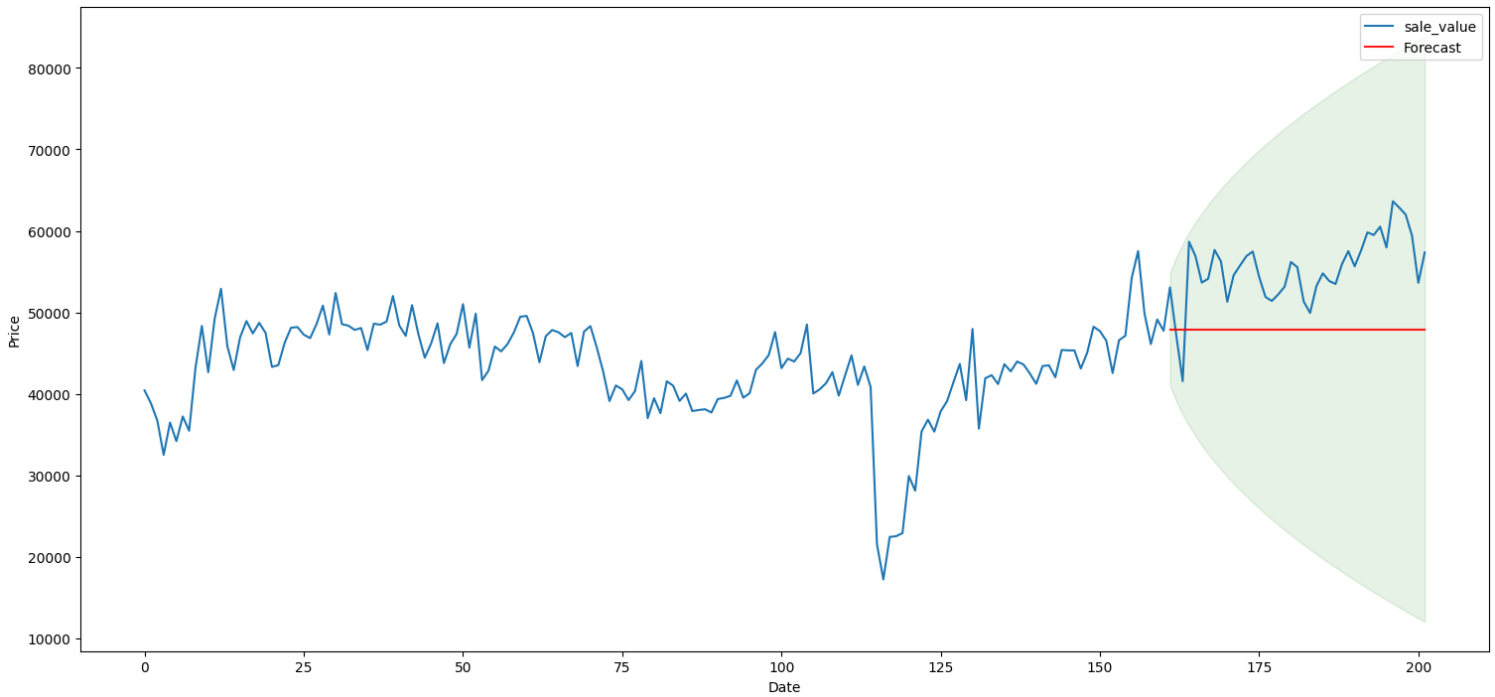
- Root Mean Square Error (RMSE) - measures predictive accuracy by capturing the average magnitude of error
- Akaike Information Criterion (AIC) - evaluates the model's goodness of fit while penalizing complexity

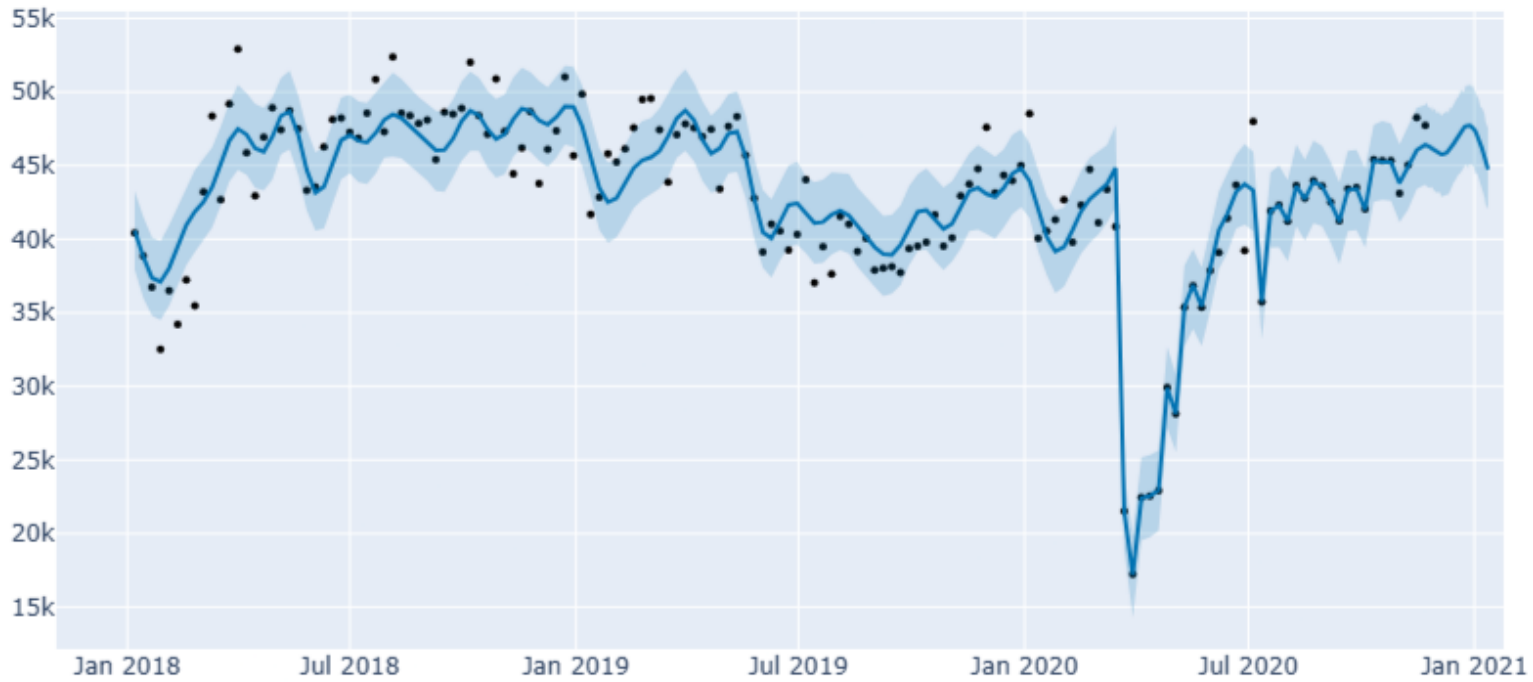
Building ARIMA

AutoARIMA from the Python module ”pmdarima” automates parameter selection based on optimizing AIC scores.



Building Prophet

After training models without accounting for the COVID-19 lockdowns, we tried to incorporate them as custom one-off holiday periods. Those models took into account the dip in sales in 2020.



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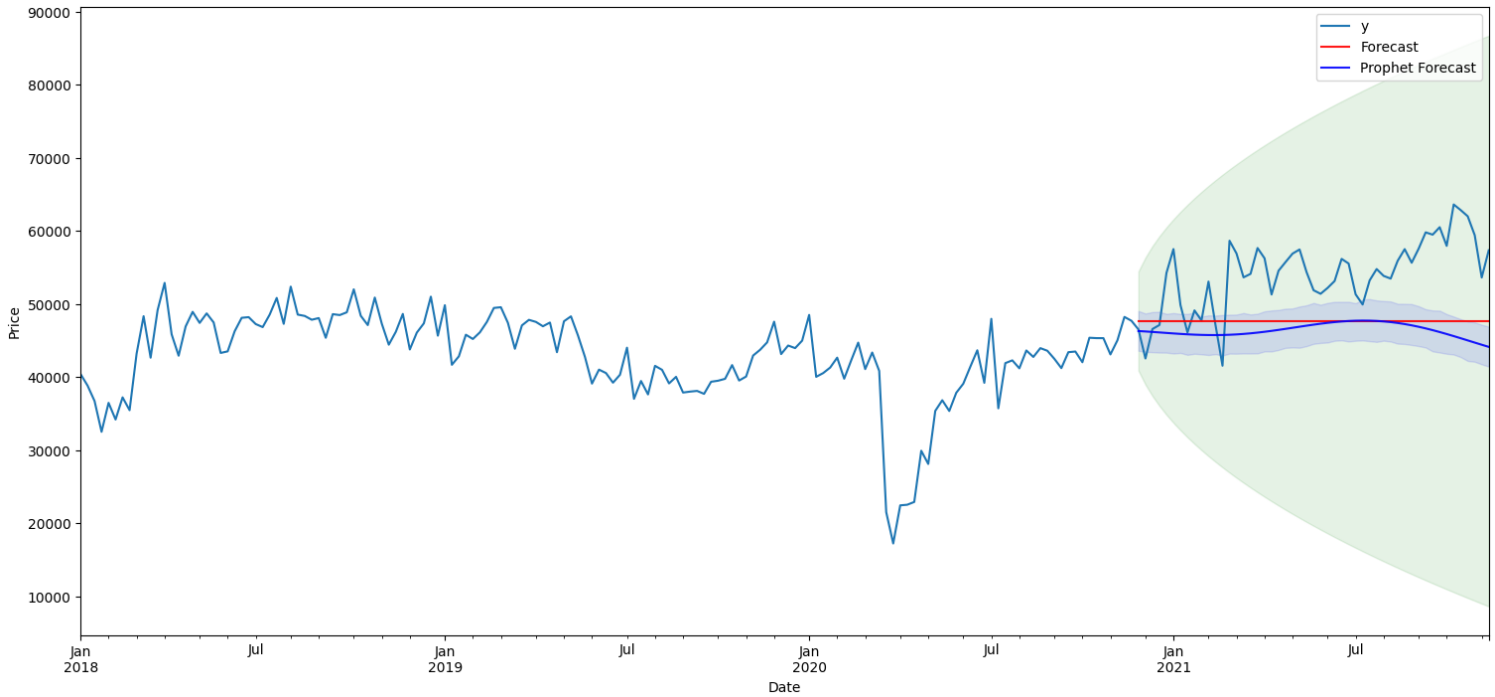
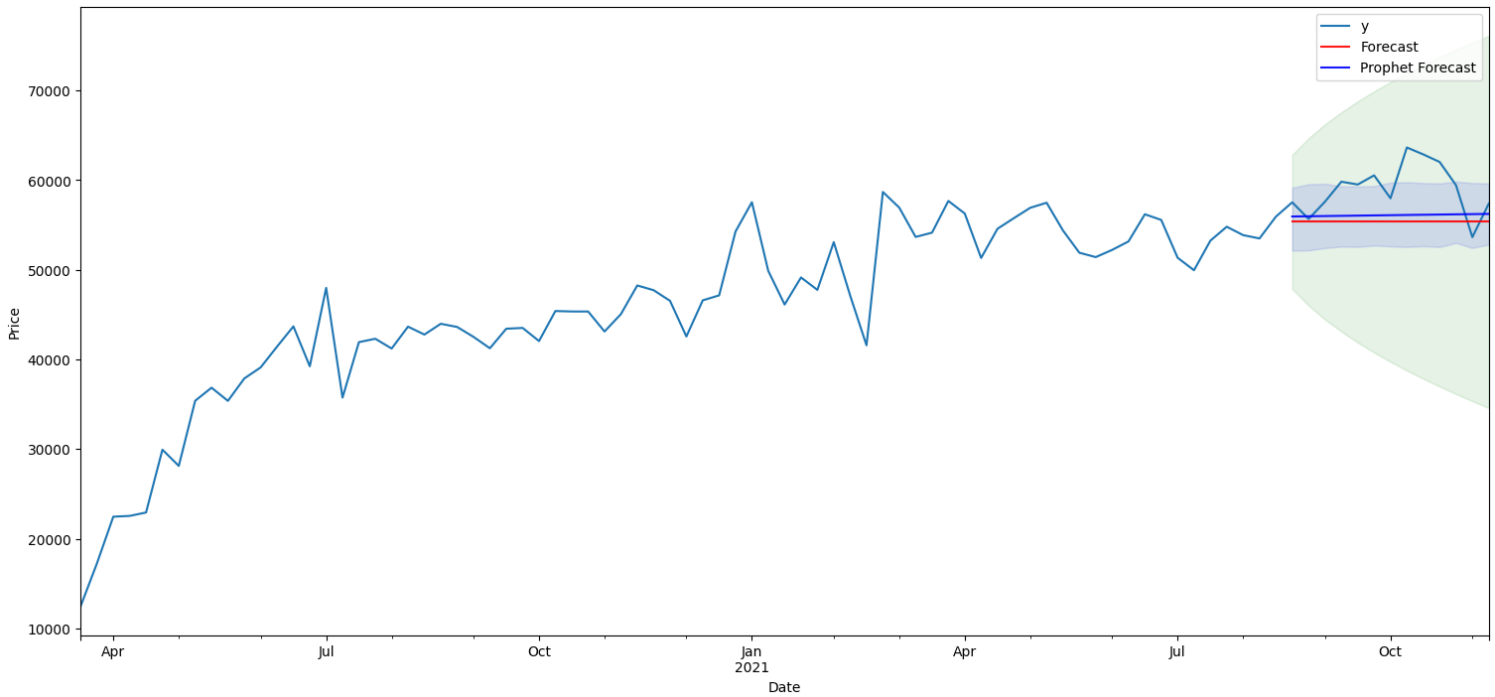
2. ARIMA's linear approach limited its ability to capture non-linear patterns.
3. Weekly aggregation helped reduce noise, thus had the lowest AIC and RMSE scores.

ARIMA VS Prophet



Finalized Models

The initial test train split was inadequate because the data had a sudden change in trend very close to the split date. To ensure model efficacy the models were also trained on just the original test data to see if it could accurately capture the new trend.



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  - Size
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  - Size
  - Variety
- Further research into other models used for time-series data

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- Both types of models tend to capture similar trends, but with varying levels of granularity and confidence.
- ARIMA casts a far wider net, so to speak, and as such values are far more likely to fall in its confidence interval.
- Prophet, on the other hand, tends to be more confident in its prediction and can produce a more nuanced forecast. This allows it to capture smaller, temporary noise slightly better as a result.